09/830413

JC08 Rec'd PCT/PTO 27 APR 2001

SUBSTITUTE SPECIFICATION

TITLE OF THE INVENTION

System for determining parameters of a technical system

BACKGROUND OF THE INVENTION

FIELD OF THE INVENTION

The invention relates to a method and system for determining parameters of a technical system.

DESCRIPTION OF THE RELATED ART

During multichannel transmission and multichannel reception of signals, interference frequently occurs, for example, between the signals/images. One typical example in this case is mixing of a voice signal with noise, which can present a major problem in telecommunications and in video conferences. The present invention thus relates to the field of signal separation in order, for example, to recover an original voice signal.

Typical known techniques for separation of source signals based on mixed signals are based on time averaging or filtering of the signals. This intrinsically has disadvantages in terms of the computation complexity.

Methods based on so-called blind channel equalization (signal equalization without prior knowledge of the transmission channel) are also known, but these methods always require a certain amount of knowledge about the source signals, such as knowledge about their statistical distribution.

The problem of signal separation also occurs, for example, when two speakers are speaking into two microphones positioned at a distance from one another, so that each microphone receives a mixture of the signals spoken by the two speakers. The problem thus arises of separating the signal mixture once again, that is to say of separating a set of superimposed input signals. L. Molgedey, H.G. Schuster, "Separation of a Mixture of Independent Signals using Time-Delayed Correlations", Phys. Ref. Lett. 72, 3634 (1994) in this case discloses the following method: the problem of separating n superimposed and correlated source signals (input signals) and at the same time of establishing mixing

09830413 . 042701

coefficients of the source intensities can be reduced to an intrinsic value problem, in which two symmetrical n x n matrices must be diagonalized simultaneously. The matrix elements are measurable time-delayed correlation functions. This intrinsic value problem can be solved by a neural network, in which case the learning rules for the lateral inhibiting interactions between the neurons can be established by a Liapunov function whose minima provide the (degenerate) solutions to the problem.

This method has also already been applied to the acoustic input signals (see F. Ehlers, H.G. Schuster, "Blind Separation of convolutive mixtures and an application in automatic speech recognition", IEEE Trans. Signal Proc. (1997).

DE 195 31 388 C1 discloses a signal separation method and a signal separation device for nonlinear mixtures of unknown signals (blind channel), which is illustrated schematically in Figure 3.

This German Patent relates to the separation of a signal mixture comprising the nonlinear superimposition of M unknown source signals X1, X2, where N ($N \geq M$) different mixtures of M source signals X1, X2 including any interference signal which may be present are supplied to a signal evaluation device, which analyzes the signal statistically to establish the nonlinear transmission factors and using these calculated factors to reverse the mixing process, so that the N outputs of the signal separation device contain, as approximately as possible, the M source signals without superimpositions.

It thus becomes possible to treat nonlinear mixtures, in which case the term nonlinear means that the source signals X1, X2 are mixed by an unknown nonlinear system G. The unknown system G is described by a so-called Volterra series, and the signal separation device G-1 establishes the coefficients in the Volterra series. Once this is known, it is possible to unmix the signal mixture. Furthermore, the coefficients can be used for further analysis in order to determine the position or speed of the signal sources.

The method which is known from this document in this case essentially comprises two steps:

Firstly, the nonlinear equations which are selected uniquely by the selectable degree of nonlinearity in the mixing process are solved by a sliding time window, and the solutions are

averaged over this time. This time averaging process represents a major disadvantage of this known technique, since it increases the computation complexity, while at the same time increasing the time required for the calculation process.

Secondly, the potential formed from a sufficiently large number of different cumulants of the estimated output signals is minimized, with the values required to calculate the potential originating from a sliding time window whose length can be varied. In this case, it is assumed that the mixing system varies sufficiently slowly that this change can be ignored in the calculation of the sought mixing factors. According to this German Patent, the second said step is carried out by constructing and minimizing a cost function. When the global minimum is reached, the optimum values, in this case the transmission factors, have been found.

With regard to the time involved and the computation complexity, the method described in DE 195 31 388 C1 is disadvantageous, since the time averaging process has to be carried out at the end of the first method step mentioned above.

SUMMARY OF THE INVENTION

The present invention is thus based on the object of providing a method and system which allow the separation of superimposed, statistically mutually independent, acoustic signals with reduced computation complexity.

This object is achieved by a method for determining parameters of a technical system by determining output signals from a set of superimposed, statistically mutually independent input signals. The parameters are determined in such a manner that the statistical independence of the output signals is maximized.

A system for determining parameters of a technical system, in which output signals can be determined from a set of superimposed, statistically mutually independent input signals, has a processor that determines the parameters in such a manner that the statistical independence of the output signals is maximized. The parameters are preferably determined using an iterative method.

In a further refinement, the parameters are elements in an unmixing matrix, by which the set of superimposed input signals is multiplied or else convoluted, by which the output

signals are formed. The optimization of the parameters in the unmixing matrix is preferably obtained by the following steps:

- repetition of a time-delayed decorrelation calculation in order to determine the intrinsic values in the unmixing matrix,

- determination of the intrinsic values in the unmixing matrix for which cross-correlations assume a minimum value, and

- carrying out cumulant minimization, with the intrinsic values determined in the previous step being used as start values for the cumulant minimization.

The cumulant minimization can be used, for example, by training a neural network, or else by any other known minimization technique, such as gradient descent or Monte Carlo simulations.

In one development, at least one diagonal parameter of the unmixing matrix is set to a predetermined value during the optimization of the parameters in the unmixing matrix, thus ensuring the stability of the minimization process with respect to a global minimum.

The unmixing matrix is preferably limited to a finite impulse response, that is to say an FIR filter (Finite Impulse Response) is used to form the individual components of the unmixing matrix. The FIR filter may be either a causal FIR filter or else a non-causal FIR filter.

Furthermore, the unmixing matrix is preferably stabilized by projection on to a unit circle during the cumulant minimization process.

The developments apply not only to the method but also to a system in which a processor is set up in such a manner that the method can be carried out.

The invention and its developments can advantageously be used for separation of superimposed, statistically mutually independent input signals, in particular acoustic input signals.

The method and the system can be used for any desired number of input signals.

10724023.040601

BRIEF DESCRIPTION OF THE DRAWINGS

These and other objects and advantages of the present invention will become more apparent and more readily appreciated from the following description of the preferred embodiments, taken in conjunction with the accompanying drawings, in which:

Figure 1 shows the use of a system for separation of superimposed, statistically mutually independent acoustic signals according to the exemplary embodiment,

Figure 2 shows a schematic illustration of the system from Figure 1, and

Figure 3 shows a signal separation device, which is known from the prior art (DE 195 31 388 C1), for nonlinear mixtures of unknown signals.

DESCRIPTION OF THE PREFERRED EMBODIMENTS

Reference will now be made in detail to the preferred embodiments of the present invention, examples of which are illustrated in the accompanying drawings, wherein like reference numerals refer to like elements throughout.

The statistical independence between the source signals (the original voice signal and the noise), also referred to as input signals in the following text, is used to recover the original voice signal from a mixture of signals, and the inverse process to that of the dynamic system, which has resulted in the mixing of the signals, is trained essentially approximately (is learnt). Two different mixtures of the voice signal and of the noise signal are obtained, for example, by two microphones 1, 2 (see Figure 1) which are at a distance from one another and/or are aligned in opposite directions. The so-called time-delayed decorrelation technique (TDD) is used to initiate the learning phase in the method, that is to say in order to determine and specify start values for the learning phase, which allows the computation complexity for cumulant minimization as described in the following text to be reduced, and allows the risk of local minima to be reduced.

Figure 1 shows two microphones 1, 2, which pick up a first input signal Z1(t) and a second input signal Z2(t). These input signals Z1(t) and Z2(t) can in turn each be mixed with one another and with noise, as is represented symbolically by a mixing matrix S (see reference symbol 3) in Figure 1. After reception and/or transmission, a set X1(t) and X2(t) of

superimposed, statistically mutually independent input signals $Z1(t)$ and $Z2(t)$ is obtained. These signals are entered in a calculation unit 4, in which essentially two steps are carried out, as is represented symbolically by a calculation unit B (reference symbol 6) for the first step and a neural network 5 for the second step.

The calculation unit 4 determines two output signals $Y1(t)$ and $Y2(t)$, respectively, which are approximately equal to the input signals $Z1(t)$ and $Z2(t)$, respectively, when the parameters are set optimally in the calculation unit 4. In other words, when the parameters of the matrices which are used are set optimally in the calculation unit 4, this calculation unit 4 essentially carries out the inverse process to that of the dynamic mixing process, which is represented symbolically by the matrix S (reference symbol 3). The exemplary embodiment relates to the optimization process for setting the parameters for the unmixing matrix.

The parameters of the matrices in the calculation unit 4 are in this case optimized such that the statistical independence between the output signals $Y1(t)$, $Y2(t)$ obtained by the matrix process in the calculation unit 4 is maximized. To this end, the output signals $Y1(t)$ and $Y2(t)$, respectively, are fed back to the calculation unit 4 (see the feedback loops 7 and 8, respectively). An iterative method is used to determine whether the statistical independence of the output signal $Y1(t)$ and $Y2(t)$, respectively, has increased in comparison to the previous iteration step (so that the iteration is in the "right" direction, in the direction of the global minimum of a cost function, which will be described in the following text).

Figure 2 shows a mathematical representation of the layout from Figure 1, in which case the mixing process 3 can be described mathematically by a matrix $S(q)$, and the unmixing process, which is intended to be carried out by the calculation unit 4, is symbolized by an unmixing matrix $M(q)$.

Figure 2 thus illustrates the problem of separation of a so-called multichannel blind source (multiple channel source without a-priori knowledge) into two dimensions. In this case, it is assumed that the mixing system $S(q)$, where q represents a unit delay, is stable and, at the same time, also has a stable inversion, that is to say it is a minimal phase system. Furthermore, it is assumed that the input signals $Z1(t)$ and $Z2(t)$ (for example a voice signal and a noise signal) are statistically mutually independent and do not have a Gaussian

distribution. The sets X1(t) and X2(t) of superimposed input signals Z1(t) and Z2(t) are input signals to an unmixing system having an unmixing matrix M(q) whose parameters (matrix elements) are trained to maximize the statistical independence between the output signals Y1(t) and Y2(t). In this case, the term "training" means the well known learning process of, for example, a neural network, which should be cited as an example of a technique to maximize the statistical independence. This is done by minimizing a cost function J(M), which will be described further below.

A cumulant cost function is formed, which minimizes the diagonal cumulant elements of the cumulant order 2-4:

$$\mathrm{Dcum} \approx J(M) = \sum_{i=1}^{4} \sum_{nondiag} \left[c^{(i)}_{nondiag}\right]^2$$

The following aspects of dynamic mixing by the mixing matrix S(q) need to be taken into account in this case:

- Stability of the unmixing system:

This is achieved by limiting M(q) to a finite impulse response (FIR filter). The stability of the FIR system M(q) can, furthermore, also be obtained by carrying out a projection on to a unit circle during the learning phase. Any non-causality of the inversion of S(q) which may be present can be compensated for by a suitable time shift (delay) to the input signal X(t).

- Uniqueness of the separated signals Y(t):

In the case of steady-state mixing processes, the original source signals are recovered by scaling. For dynamic unmixing, the risk of the separated signals Y(t) not being unique is even greater. It is obvious that, in the situation where Y1(t) and Y2(t) are statistically mutually independent, any linear-filtered modification of these signals will also still be statistically independent. Additional information is therefore required in order to reduce the inherent ambiguity of the problem.

- Gaussian deformation of the data:

Algorithms on a cumulant basis for steady-state blind source separation effectively minimize or eliminate higher-order diagonal cumulants corresponding to the output signals Y(t). On the other hand, linear filtering leads to the data being deformed to a Gaussian distribution, with the higher-order cumulants moving in the 0 direction. This can thus lead to limit solutions, in which the cost function reaches local minimum, but with the desired actual separation (global minimum) not being achieved. In order to avoid this undesirable situation, the structure of the unmixing transfer function (unmixing matrix) M(q) is subject to a number of limitations.

In order to avoid the abovementioned problems, an approach is chosen in which at least one (or else all) of the diagonal elements is or are set to the unit value:

M11(q) = 1 and M22(q) = 1.

This assumption is exact if the mixing elements S11(q) and/or S22(q) likewise have a unit value "1". Otherwise, it is assumed that S11(q) and/or S22(q) have stable inversions, which allows the diagonal elements to be scaled from M(q) to the unit value. This approach considerably reduces the ambiguity of a solution and, furthermore, effectively avoids the risk of excessive Gaussian-distribution deformation of the output signals. Even if, as stated above, the limitation to the diagonal elements of M(q) is at first glance to be highly restrictive, this assumption is generally satisfied in practical use. One typical example is the removal of noise from voice signals on the basis of a recording using two microphones, with the microphones being physically separated from one another or one microphone pointing in the direction of the speaker, while the other microphone points in the opposite direction, so that the second signal, facing away from the speaker, essentially includes only a noise signal.

The cumulant approach is based on the direct determination of the diagonal cumulant, as is stated in the article mentioned initially by F. Ehlers and H. Schuster, "Blind Separation of convolutive mixtures and an application in automatic speech recognition", IEEE Trans. Signal Proc. (1997), although this inherently has the disadvantage that numerical solution is highly complex. Suitable initialization is thus used for this minimization method. In order to determine start values for the minimization method, the present invention uses the technique of

10/27403.3S9S0

time-delay decorrelation (TDD) for simultaneous decorrelation of two different time delays, in which case this TDD technique can be based on a suitable matrix intrinsic-value problem. As already stated, this TDD technique is used according to the present invention for initiation of the diagonal (cross-correlation) cumulant minimization problem.

In summary, the method can be subdivided into the two following steps:

1. Repetition of the TDD method on the basis of the intrinsic-value problem in the frequency domain for different delay pairs and determination of that solution for which the cross-correlation terms have a minimum value.

2. Initiation (start) of the diagonal cumulant minimization process on the basis of the start values (FIR parameters) determined in the above step.

A number of major characteristics and advantages will be summarized once again in the following text:

- No a-priori knowledge of the signal characteristics is required, with the exception of the necessity for statistical independence.

- The stability of the dynamic unmixing system is ensured by the modulation of its components as an FIR filter.

- Excessive Gaussian distribution deformation is avoided by the approach of at least one of the elements in the mixing transfer function matrix (unmixing matrix) being set to the unit value, or being able to be scaled to the unit value, and

- since the cumulant minimization step (step 2) requires a large amount of computation complexity, the learning algorithm, for example of a neural network, is initialized using the TDD method.

The following text contains a program in Matlab, e.g. Version 4, by which the exemplary embodiment described above can be implemented on a computer:

```
function { cost,out1,out2 ] } =cumulant_costFIRa2(par,input,p1,p11,p2,p22,a3,a4);
% { cost,out1,out2 ] } =cumulant_costFIRa2(par,input,p1,p11,p2,p22,a3,a4);
% cumulant cost
```

```
% FIR representation used
% filter function used in both directions (non_causal)

{ np,mp ] } =size(par);
fir1=par(1:p1);
fir11=par(1+p1:p1+p11);
fir2=par(1+p1+p11:p1+p11+p2);
fir22=par(p1+p11+p2+1:mp);
den=1;                                              %FIR only

out1= { input(:;1)-filter(fir1,den,input(:,2))-flipud(filter( { 0 fir11 ] } , { den ] }
,flipud(input(:,2)))) ] } ;
                              %/std(input(1,:));              %dlsim
%filter
out2= { input(:,2)-filter(fir2,den,input(:,1))-flipud(filter( { 0 fir22 ] } , ] }  { den],
flipud(input(:,1)))) ] } ;%/std(input(:,2));
                              %dlsim     %filter
out { out1 out2 ] } ;
%out1=out1/std(out1); % this scaling was not needed in examples in SIP98 paper
%out2=out2/std(out2);

Ld=0; % number of delays in calculating the cross-correlation
cost3=0;
cost4=0;
costALL1= {  ] } ;
costALL2= {  ] } ;
o12=out1.*out2;
cost2=mean(o12)^2;
```

```
o112=out1.*out1.*out2;
o122=out1.*out2.*out2;

if a3 ==1
        cost3= { mean(o122) ] } ^2+ { mean(o122) ] } ^2;
end

if a4 ==1

        cost4= { mean(o112.*out1)-3*mean(out1.^2)*mean(o12) ] } ^2+...
{ mean((out1.^2).*(out2.^2))-2*mean(o12)^2-
mean(out1.^2)*mean(out2.^2) ] } ^+...
{ mean(o122.*out2)-3*mean(out2.^2)*mean(o12) ] } ^2;
end

%cum4a= { cum4x(out1,out1,out1,out1) ] } ^2;
%cum4b= { cum4x(out2,out2,out2,out2) ] } ^2;
cost=cost2+a3*cost3+a4*cost4;                    %-cum4a-cum4b;
```